A Granular Multi-Sensor Data Fusion Method for Life Support Systems that Enhances Situation Awareness

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Abstract

Slow-changing characteristics of controlled environmental systems and the increasing availability of data from sensors and measurements offer opportunities for the development of computational methods that enhance situation observability, decrease human workload, and support real-time decision making. Some of these methods are known as multi-sensor data fusion; they combine measurements from multiple sources to produce a more concise representation of the information contained therein. Such information can be used to design better user-centered interfaces, allowing human operators to maintain situation awareness. Situation observability enables humans to perceive and comprehend the state the system at a given instant of time, and helps human operators in deciding what actions to take at any given time that may affect the projection of such state into the near future. This paper presents a multi-sensor data fusion method that makes use of a collection of discrete human-inputs and measurements to generate a granular perception function that supports situation awareness. These human-inputs are situation- rich, meaning that they combine measurements defining the operational condition of the system with a subjective assessment of its situation. As a result, the perception function produces situation-rich signals that may be used in ecological human-interfaces or as a switching mechanism in automation strategies and fail-safe/fail-op mechanisms. The granular perception function is a fuzzy associative memory composed of a number of granules equal to the number situations that may be detected by human observers; its development is based in the interaction of human operators with the system. The human-input data sets are transformed into a fuzzy associative memory by an adaptive method based on particle swarms. The paper describes the multi-sensor data fusion method proposed and its application to a ground-based aquatic habitat working as a small-scale environmental system. Results show how this approach helps to generate signals that enhance the situation observability of the aquatic habitat.

Keywords:
Sensor fusion, granular computing, regenerative life support, switching control, human-automation systems.

1. Introduction

One of the challenges of long-duration spaceflight is the capability of habitation systems to regenerate life support consumables, such as oxygen and water[1]. *Regenerative* life support systems (RLSS) offer alternatives to recycle metabolic byproducts, such as urine, and to achieve an incremental closure of gaseous and liquid material cycles. Such *material closure* increases the autonomy of space habitats and helps reduce the frequency of resupply missions and their overall cost. An example of current RLSS is the Water Recovery System (WRS) commissioned in the U.S. segment of the International Space Station (ISS), which recycles waste liquids back into potable (drinking) water. But as researchers and engineers integrate regenerative technologies to increase system closure, new challenges arise from their operation. System closure not only entails the interconnection of complex material networks, but also increase the possibility for unintended interactions between chemical species within the habitat, leading to the accumulation of unexpected chemical compounds or depleting consumables that may affect individual life-support processes or even crew health. Such behaviors are not susceptible to prediction and are discovered as

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anomalies during their operation[2]. An example of such unintended chemical interactions is found in the 2010 WRS anomaly, caused by the accumulation of dimethylsilanediol (DMSD) in the Water Processing Assembly (WPA) of ISS[3]. Still unresolved, this anomaly may be the best example to date of unintended chemical interactions involving regenerative processes in a deployed space habitat. The problem centers on detecting such interactions early enough and on making use of such information in monitoring and automation systems.

The invention of methods to measure environmental variables by means of microsystems or optical devices tends to reduce the unit cost of novel sensor technology and opens opportunities for engineers to integrate evermore complex systems. Such innovations allow individual human operators to perform more complex tasks and to assist humans do their job through automation. This paper proposes a multi-sensor fusion method that elaborates on a granular approach to these challenges[4]. It makes use of sensor data and expert assessments to generate a granular perception function in support of situation awareness. The method employs an agent architecture based on FAM[4] in an effort to allow for *situation observability*, *i.e.* the capability of non-expert human operators to probe for information about the situation of the system. However, the abundance of sensor information may result in a combinatorial explosion unsuited for the manual design of monitoring and automation systems; the difficulty of manually defining fuzzy sets for each individual condition makes such technique impractical. Therefore, the main contribution of this paper proposes to exploit the interaction of human experts with the system to collect situation-rich data useful to represent their situation knowledge base (SKB). The SKB is then used in the perception function of the FAM-based agents to generate the switching signals that combine control laws into its integrated control signal. Those switching signals contain information about the situation of the system and may also be used in user-interfaces for human-automation coordination. This general contribution is composed of four more specific that include the following steps: (1) data collection, (2) aggregation algorithm, and (3) coherence operation. In particular, the method proposed in this paper makes use of particle swarm optimization[5] (PSO) to *compress* sensor data and a set of human-expert situation assessments into a granular representation of their SKB. In such a way, the purpose of this work is to make use of computational intelligence tools, consistent with control theory and principles in cognitive engineering, to contribute to the methodological development of situation-oriented and user-centered design approaches[6].

1.1. Background

Multi-sensor data fusion combines observations and measurements from sensors to provide a description of a system and its environment[7]. Traditional multi-sensor fusion methods are probabilistic in nature and derive from the application of tools in statistics, estimation, and control theory. These are: (1) the Bayes' rule, (2) probabilistic grids, (3) the Kalman filter, and (4) sequential Monte Carlo methods. However, a shortcoming of probabilistic methods is their apparent inability to address unknown situations, which grows in importance for anomaly detection and management. There are four main limitations for probabilistic methods in multi-sensor data fusion[7]:

1. *Complexity*: This limitation in found in the large number of probabilities required to correctly apply probabilistic reasoning.
2. *Inconsistency*: It refers to the difficulty in obtaining consistent deductions about the state of a system from sets of belief that are not necessarily consistent.
3. *Precision of models*: This refers to the difficulty to obtain system representations, primarily caused by the inability to describe probabilities of quantities for which there is not enough available information.
4. *Uncertainty about uncertainty*: It is difficult to assign probabilities in the presence of unknown unknowns and uncertainty about sources of information.

Alternative methods, such as interval calculus, fuzzy logic[8], and evidential reasoning[9–11], offer approaches that help overcome these limitations[7]. Such approaches support research efforts toward the management of large-scale/ubiquitous sensor systems and monitoring systems. This paper presents a multi-sensor data fusion method aimed at the development of monitoring and automation systems for RLSS that may especially address anomalies.

1.2. Organization

The paper is divided in six additional Sections. Section 2 introduces the FAM-based agent architecture on which the multi-sensor data fusion method proposed is developed. Section 3 presents the fusion method. Section 4 illustrates the method with an application to the model of a small-scall aquatic habitat and discusses results. Section 5 presents results and Section 6 elaborates a discussion on them. Finally, Section 7 provides concluding remarks.

2. Granular Approach to the Automation of RLSS

The monitoring and automation of RLSS motivates the application of the FAM-based agent architecture [4,12]. The architecture is characterized by a (1) perception function, (2) a set of controllers, (3) and a correspondence function. The latter associates controllers to each situation that is detected by the perception function and combines them into a single integrated control signal. Each signal is intended to drive an actuator and, consequently, for each actuator a FAM-based agent may be defined. The FAM-based agent architecture implements a switched control paradigm [13] that assigns a control action to modes of operation in which the system may perform, *i.e.* in the form of (Situation, Controller). The switching nature of the agent introduces flexibility and modularity to the system and enables an incremental development. The challenge in this case is to develop the FAM with the intention to promote the coordination of multiple agents and for their interaction with humans. Hence, the granular approach used is conceived for a situation-oriented and user-centered methodology, as will be presented in Section 3. Figure 1 shows a diagram of a single FAM-based agent with a user interface manipulating a single variable in a small-scale aquatic habitat. The diagram describes the components of the FAM-based agent consistent with Subsections 2.1, 2.2, and 2.3. Some advantages of this approach have been shown in previous work [4,12].

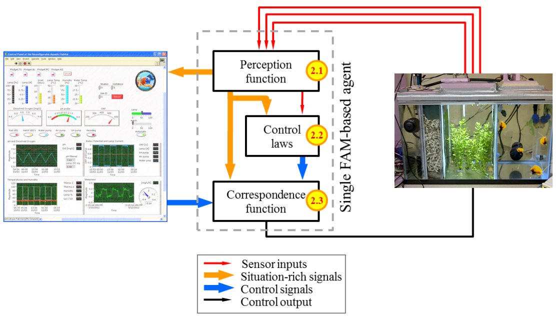


Figure 1: Diagram describing the FAM-based agent architecture and its components

2.1. *Perception Function and Granular Structure*

The FAM of the argent assumes the availability of n measurable variables x_i for $i = 1, 2, \ldots, n$ and their universes of discourse X_i so that $x_i \in X_i \subseteq \Re$, the variables being non-redundant and non-interactive: $X_i \neq X_j$; $j = 1, 2, \ldots, n$; $i \neq j$. Each universe X_i is partitioned in k_i subsets, each of which is denoted as $X_i^\alpha \subset X_i$, $\alpha = 1, 2, \ldots, k_i$. Continuous membership functions describe each one of the subsets as $\mu_{X_i^\alpha}(x_i)$, which are normal and convex [14]. The partitions are assumed *coherent*, *i.e.* they comply with the Ruspini condition [15]:

$$\sum_{\alpha=1}^{k_i} \mu_{X_i^\alpha}(x_i) = 1 \qquad \forall i = 1, 2, \ldots, n \tag{1}$$

As a consequence, a number of l possible situations or operating conditions can defined as granules or non-interactive fuzzy sets $\tilde{A}_j$, for $j = 1, 2, \ldots, l$. The l situations are the result of the Cartesian product performed on the combination of the subsets X_i^α in X_i. The Cartesian product is implemented with the *minimum* operator presented in Equation 2, for $l = \prod_{i=1}^{n} = k_i = k_1 \cdot k_2 \cdot \cdots \cdot k_n$.

$$\tilde{A}_j\left(x_1, \ldots, x_n\right) = \min_{\substack{i=1,\ldots,n \\ \alpha=1,2,\ldots,k_i}} \left(\mu_{X_i^\alpha}\left(x_i\right)\right) \tag{2}$$

The set $\tilde{A} = \{\tilde{A}_j\}$ contains the granular structure in which each granule $\tilde{A}_j$ describes a different situation and a percept of the FAM-based agent.

2.2. *Control Signals*

In the same fashion, a set of control signals $U = \{u_j\}$ is defined for up to l different control laws. Controllers generate signals u_j that correspond to each condition $\tilde{A}_j$. These signals may be treated modularly to form the set $U = \{u_1, u_2, \ldots, u_l\}$, with the maximum number of different control signals limited by l. The error modulation solution [16] or a similar technique is required for controllers with integral control action. This prevents unnecessary accumulation in these control signals that may result in unstable behaviors. Additional considerations on switched control [13,17] should be included in this component of the FAM-based agent and in the correspondence function Ω described in the next Subsection.

2.3. *Correspondence Function and Control Signal*

With the sets $\tilde{A}$ and U defined, the Correspondence Function Ω can be expressed as a rule-base or in pairs (Situation, Control Signal) as in Equation 3.

$$\begin{aligned} &\Omega : \tilde{A} \to U \\ &\Omega = \left\{\Omega_j\right\} = \left\{\left(\tilde{A}_j\left(x_1, \ldots, x_n\right), u_j(t)\right)\right\} \end{aligned} \tag{3}$$

The integrated control signal u_I is obtained from applying the weighted average technique to the defuzzification of the FAM. The signal u_I drives a single actuator in the system. Thus, the aggregation of FAM-based agents associated to each actuator of a system composes a FAM-based multi-agent system. The weights used in Equation 4 are the membership values of each corresponding situation, i.e. $\mu_{\tilde{A}_i}(x_1, \ldots, x_n)$, and the weighted arguments are their corresponding control signals, $u_j(t)$.

$$u_I(x_1, \ldots, x_n, t) = \frac{\sum_{i=1}^{l} \mu_{\tilde{A}_i}(x_1, \ldots, x_n) \cdot u_i(t)}{\sum_{i=1}^{l} \mu_{\tilde{A}_i}(x_1, \ldots, x_n)} \quad (4)$$

3. Granular Multi-Sensor Data Fusion Method

The perception function of the FAM-based agent architecture can also be described as a granular multi-sensor data fusion module. Such approach has the advantage to combine data from a large number of sensors. However, such same advantage poses a challenge and makes impractical to manually define membership functions $\mu_{X_i^\alpha}(x_i)$ for situations that may be detected. This paper proposes the use of human-system interaction and the application of methods in computational intelligence to overcome this challenge. Figure 2 shows a diagram of the methodology proposed. The diagram describes the steps used, consistent with Subsections 3.1, 3.2, 3.3, and with Section 4.

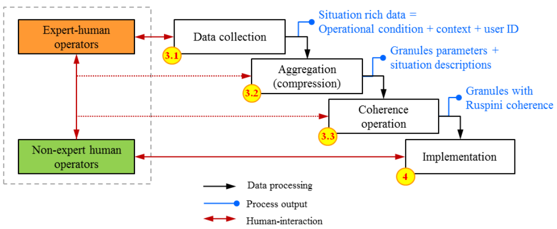


Figure 2: Human-system interaction and granular multi-sensor fusion method.

The method proposes the collection situation assessments from expert human operators, i.e. system snapshots, to obtain situation-rich datasets useful to generate a granular structure that represents the SKB of the experts. The parameters describing such granular structure are obtained from the aggregation (compression) by employing a particle swarm optimization algorithm. The result is a granular structure useful for decision support tools and to define the Ruspini partitions of the perception function in FAM-based agents. The following Subsections describe each one of these steps.

3.1. Data Collection

Data collection takes advantage of the interaction between expert human operators and the system to obtain situation-rich datasets. Such datasets include the following information: (1) measurements from sensors about the *operating condition* of the system, (2) its *context* (external state) represented by a situation code, and an *identifier* for each expert. Datasets contain N snapshots of the system recorded at times t_j for $j = 1, 2, \ldots, N$, as shown in Figure 3.

	Measurements					Expert Input		
	Time	x_1	x_2	$\cdots$	x_n	Situation	Confidence	User Code
Dataset	t_1	x_{11}	x_{21}	$\cdots$	x_{n1}	s_1	c_1	h_1
	t_2	x_{12}	x_{22}	$\cdots$	x_{n2}	s_2	c_2	h_2
	$\vdots$	$\vdots$	$\vdots$		$\vdots$	$\vdots$	$\vdots$	$\vdots$
	t_N	x_{1N}	x_{2N}	$\cdots$	x_{nN}	s_G	c_N	h_N

Figure 3: Illustration of a data set resulting from the data collection process

The measurements from sensors x_i are denoted as x_{ij}, for $i = 1, 2, \ldots, n$. If a sensor measurement would not be electronically available, these values may also be manually introduced by the expert through a user interface. In addition to sensor measurements, the dataset includes assessments defining situation codes s_γ, for $\gamma = 1, 2, ..., G$. These values are accompanied by the degree of confidence $c_j \in [0, 1]$. If $c_j = 1$, the expert is fully confident that the system snapshot taken at t_j belongs to situation s_γ. The number $G \geq l$ depends on the presence of *levels of resolution* in the situation assessments[18]; *i.e.* a granule defined as "nominal" may be subdivided in subgranules, such as "nominal-high" and "nominal-low." This paper makes $G = l$, and does not address hierarchical granular structures. Finally, the user code h_j allows to identify the number of human experts contributing to the dataset, enabling for crowdsourcing techniques[19,20].

3.2. Aggregation or Data Compression

The aggregation algorithm compresses the situation-rich datasets collected into granular structures described by an array of parameters that define membership functions $\mu_{X_i^\alpha}$ for each situation γ susceptible for detection by sensors i and human experts. The following Subsections describe how SKB is represented, how it is obtained from datasets, and suggests an approach to achieve coherence.

3.2.1. Knowledge Representation

The adaptation of the situation-rich datasets to a granular structure requires flexibility in the membership function $\mu_{X_i^\alpha}$ used to describe such information. Therefore, knowledge representation is achieved by employing π-membership functions, defined in Equation 5.

$$\mu_{X_i^\alpha} = \begin{cases} 0 & x_i \le a \\ 2\left(\frac{x_i-a}{b-a}\right)^2 & a < x_i \le \frac{a+b}{2} \\ 1-2\left(\frac{x_i-b}{b-a}\right)^2 & \frac{a+b}{2} < x_i \le b \\ 1 & b < x_i \le c \\ 1-2\left(\frac{x_i-c}{d-c}\right)^2 & c < x_i \le \frac{c+d}{2} \\ 2\left(\frac{x_i-d}{d-c}\right)^2 & \frac{c+d}{2} < x_i \le d \\ 0 & x_i \ge d \end{cases} \tag{5}$$

The plot of a π-membership function is shown in Figure 4, showing the parameters $P = [a, b, c, d]$ that define the "feet" and "shoulders" of its curve. Each membership function in the aggregation process represents a unique situation $\gamma = 1, ..., G$ for a single sensor x_i. A PSO algorithm is used to obtain the four parameters of each membership function, as described in the following Subsection.

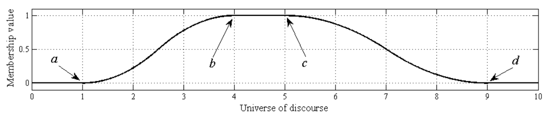


Figure 4: π-Membership function with parameters $P = [a, b, c, d] = [1, 4, 5, 9]$.

3.2.2. Particle Swarm Optimization

The process that adapts the *pi*-membership function to the dataset corresponding to a situation detected by a sensor is a PSO[5] algorithm. Given a situation γ and a sensor i, the problem consists of finding $P^* \in X_i$ such that Equation 6 satisfied, with $f(x_i) = \sum\left(\mu_{X_i^\alpha}(x_{ij}) - c_j\right)^2$ for $j = 1, 2, \ldots, N$ and with the initial constraints shown in Table 1.

$$\begin{aligned} P^* &= \arg\min_{x_i \in X_i} f(x_i) \\ &= \{x_i^* \in X_i : f(x_i^*) \le f(x_i) \forall x_i \in X_i\} \end{aligned} \tag{6}$$

	Constraints
1:	$a \le b \le c \le d$
2:	$\min x_{ij} - 0.25\left\|\max x_{ij} - \min x_{ij}\right\| \le a \le \min x_{ij}$
3:	$\min x_{ij} \le b \le \max x_{ij}$; $\min x_{ij} \le c \le \max x_{ij}$
4:	$\max x_{ij} \le d \le \max x_{ij} + 0.25\left\|\max x_{ij} - \min x_{ij}\right\|$

Table 1: Initial constraints of the particle swarm optimization.

The parameters of the particle swarm are $W = 0.99$, $\varphi = 0.02$ and a random variable a random variable $\zeta_1 \in [0, 1]$ that also defines $\zeta_2 = 1 - \zeta_1$. The algorithm is implemented with the steps enumerated in Table 2, where p represents a particle in the population.

Step	Description
1.	Randomly distribute particle swarm (or swarm of agents) in the search space.
2.	Evaluate the performance of each particle according to $f(x_i)$.
3.	If the current position is better than previous ones, then update with the best.
4.	Determine the best particle so far according to their previous and present positions.
5.	Update velocities with $v_p^{t+1} = W \cdot v_p^t +$ $+\varphi\left[\zeta_1\left(x_{lp}^t - x_p^t\right) + \zeta_2\left(x_g^t - x_p^t\right)\right]$
6.	Update positions of particles according to $x_p^{t+1} = x_p^t + v_p^{t+1}$.
7.	Repeat from (2) until $f(x_i^*) < \frac{\left\|\max x_{ij} - \min x_{ij}\right\|}{500}$ or iterations = 2000.

Table 2: Particle swarm optimization algorithm

The process results in a granular structure with dimensions $G \times n \times 4$ as shown in Figure 5. Although the PSO may converge to a "best" result, the aggregation process is insufficient to guarantee Ruspini partitions (see Section 2.1). Therefore, a coherence operation becomes necessary to arrive at partitions that may be useful beyond monitoring tasks, i.e. granular automation systems. One of the advantages of using PSO is the flexibility it provides to vary the computer power invested in the aggregation process. Its disadvantage is that PSO is a meta-heuristic search that may not necessarily arrive at the optimum solution, unless enough computer power is invested; i.e. using a large population of particles and allowing them to communicate globally.

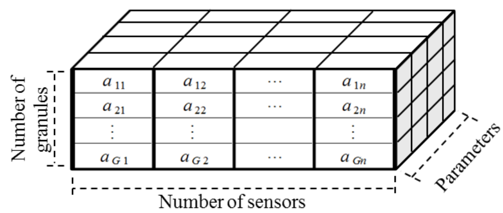


Figure 5: Three dimensional array containing granular structure

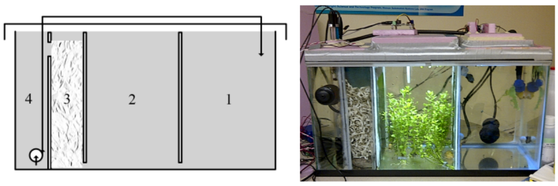
3.3. Coherence Operation

The coherence operation adjusts parameters P of each fuzzy set $\mu_{X_i^\alpha}$ according to their similarity and proximity. This is achieved by performing operations on the parameters $P = [a, b, c, d]$ of the π-membership functions. For example, the similarity between two fuzzy sets with parameters P' and P'' can be determined by $\min(P'') < \bar{P}' < \max(P'')$, where $\bar{P}'$ is the average of the parameters of P'. Future research will further elaborate on granular computing solutions to this operation with the purpose of obtaining Ruspini partitions. Section 4 presents results from a numerical example that supports this objective.

4. Implementation in a Small-Scale Aquatic Habitat

4.1. Preliminary Description of the Aquatic Habitat

In order to illustrate the methodology presented in Section 3, this Section makes use of the mathematical model of a aquatic habitat[21] that focuses on the process of respiration. On one hand, animals consume dissolved oxygen (DO) is consumed while exhaling CO_2 as a byproduct. On the other hand, photosynthesis is promoted by using an LED-lamp to irradiate plants, produce DO from CO_2, and thus regulate the oxygen needed by all consumers. An advantage of using the aquatic habitat as a small-scale RLSS research platform is its ability to isolate a small ecosystem in a volume of water, where life support compounds can be stored (dissolved). The water serves as the media through which these compounds are exchanged between the organisms. The habitat is a 10-gallon tank divided in four compartments by three separators that allow the water to circulate, as shown in Figure 6.



(a) (b)

Figure 6: (a) Recirculation diagram of the habitat; (b) Physical realization of the habitat.

In this platform, the first compartment holds animals (consumers) while the second one contains plants (producers) of the *Bacopa Monnierii* species. The third compartment serves the purpose of a mechanical, biological and chemical filter, and the fourth compartment holds the volume of water where the measurements are taken with sensors. The variables measured include dissolved oxygen (DO), pH, oxidation reduction potential (ORP), and water temperature, among others. The water flows through the four compartments and a water pump circulates it from the fourth back into the first compartment. The first compartment also has a 10×10 [cm] motorized hatch and an aerator that makes the system open or closed. The hatch/aerator mechanism is used as a fail-safe mechanism for DO levels below 2.0 [mg/L]. The second compartment is irradiated by a neutral-white spectrum LED-lamp that promotes photosynthesis on plants; this compartment also enables the addition of carbonate solution through a dosifier pump. Changes in the carbonate hardness (kH) in the water are monitored through changes in the pH readings. A computer receives the sensor readings and automates the aquatic habitat. The habitat may also be manually controlled through a graphical user interface (GUI).

4.2. Dynamic Model of the Aquatic Habitat

The model of the habitat[21] is described as the switching system in Equation 7, where x are substances, such as dissolved oxygen or carbon dioxide, and $[x]$ their concentration in [mg/L].

$$\frac{d}{dt}[\vec{x}] = \begin{cases} [A]_{cr}\,[\vec{x}] + [B]\,\vec{x} & \text{closed; recirculating} \\ [A]_{cd}\,[\vec{x}] + [B]\,\vec{x} & \text{closed; diffusive} \\ [A]_{or}\,[\vec{x}] + [B]\,\vec{x} + \vec{r}_g & \text{open; recirculating} \\ [A]_{od}\,[\vec{x}] + [B]\,\vec{x} + \vec{r}_g & \text{open; diffusive} \end{cases} \tag{7}$$

Its matrices and vectors are as follows:

$$[A]_{cr} = \begin{bmatrix} -\frac{F}{A_1 h} & 0 & 0 & \frac{F}{A_1 h} \\ \frac{F}{A_2 h} & -\frac{F}{A_2 h} & 0 & 0 \\ 0 & \frac{F}{A_3 h} & -\frac{F}{A_3 h} & 0 \\ 0 & 0 & \frac{F}{A_4 h} & -\frac{F}{A_4 h} \end{bmatrix}$$

$$[A]_{cd} = \begin{bmatrix} -\frac{DA_{s_a}}{A_1 h} & \frac{DA_{s_a}}{A_1 h} & 0 & 0 \\ -\frac{DA_{s_a}}{A_2 h} & 0 & \frac{DA_{s_a}}{A_2 h} & 0 \\ 0 & -\frac{DA_{s_a}}{A_3 h} & -\frac{D}{A_3 h}\left(A_{s_a} - A_{s_b}\right) & \frac{DA_{s_b}}{A_3 h} \\ 0 & 0 & -\frac{DA_{s_b}}{A_4 h} & \frac{DA_{s_b}}{A_4 h} \end{bmatrix}$$

$$[A]_{or} = \begin{bmatrix} -\frac{1}{h}\left(\frac{F}{A_1} + k_v\right) & 0 & 0 & \frac{F}{A_1 h} \\ \frac{F}{A_2 h} & -\frac{F}{A_2 h} & 0 & 0 \\ 0 & \frac{F}{A_3 h} & -\frac{F}{A_3 h} & 0 \\ 0 & 0 & \frac{F}{A_4 h} & -\frac{F}{A_4 h} \end{bmatrix}$$

$$[A]_{od} = \begin{bmatrix} -\frac{\left(\frac{DA_{s_a}}{A_1} + k_v\right)}{h} & \frac{DA_{s_a}}{A_1 h} & 0 & 0 \\ -\frac{DA_{s_a}}{A_2 h} & 0 & \frac{DA_{s_a}}{A_2 h} & 0 \\ 0 & -\frac{DA_{s_a}}{A_3 h} & \frac{D\left(A_{s_b} - A_{s_a}\right)}{A_3 h} & \frac{DA_{s_b}}{A_3 h} \\ 0 & 0 & -\frac{DA_{s_b}}{A_4 h} & \frac{DA_{s_b}}{A_4 h} \end{bmatrix}$$

$$[B] = \begin{bmatrix} \frac{1}{A_1 h} & 0 & 0 & 0 \\ 0 & \frac{1}{A_2 h} & 0 & 0 \\ 0 & 0 & \frac{1}{A_3 h} & 0 \\ 0 & 0 & 0 & \frac{1}{A_4 h} \end{bmatrix}$$

$$[\vec{x}] = \begin{bmatrix} [x]_1 & [x]_2 & [x]_3 & [x]_4 \end{bmatrix}^T$$

$$\vec{x} = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix}^T$$

$$\vec{r}_g = \begin{bmatrix} \frac{k_v [x]_g}{h} & 0 & 0 & 0 \end{bmatrix}$$

The assumptions are the following: (a) the recirculation flow is assumed laminar; (b) water density is constant; (c) the recirculation flow is the same for all compartments; (d) liquid solutions are perfectly well-mixed in all compartments; (e) output concentrations are those inside each compartment; (f) the water level of all compartments is the same and constant; (g) the volume of the compartments is constant. The first two separators have openings with cross sectional areas A_{s_a}, and the third A_{s_b}. The model is implemented making use of the parameters listed in Table 3.

The substances x considered in the mathematical model are dissolved oxygen (DO), carbon dioxide (CD) and carbonate hardness (kH). The output equation is $y = [[DO]_4 \; pH_4 \; [kH]_4]^T$, where the conversion from $[CD]_4$ into pH is given by[22] $pH_4 = 6.3 - log([CD]_4/[kH]_4)$. The equation for pH is valid within a 5-10% accuracy for $6.5 \leq pH \leq 9.5$. The vector $\vec{r}_g$ establishes the equivalent concentration of gases in the atmosphere (an infinite buffer) as a reference value for the volatile configuration of the system. The rates of production and consumption are presented in Table 4.

Table 3: Model parameters used in the simulation of the four compartment reconfigurable aquatic habitat.

Parameter	Value	Units	Description
h	26.28	cm	Water height
$A_1 = A_2$	533.40	cm^2	Top surface areas
$A_3 = A_4$	186.69	cm^2	Top surface areas
A_{s_a}	12.60	cm^2	Opening in sep. “a”
A_{s_b}	48.00	cm^2	Opening in sep. “b”
F	390	l/h	Pump flow rate
$[DO]_g$	8.40	mg/L	O_2 saturation conc.
$[CD]_g$	0.69	mg/L	CO_2 saturation conc.
D	1750	cm/h	Liquid diff. const.
k_v	200	cm/h	Gas diffusion const.

Table 4: Production and consumption rates for $\vec{x}$ in [mg/h]

	DO_1	CD_1	DO_2	DO_3	CD_3	kH_3
Values	-4	4	23.0	-7.0	7.0	-17

4.3. Simulations Performed on the Model of the Habitat

The simulations performed on the model of the habitat are divided in two. A first simulation performing the granular multi-sensor data fusion method is presented in Subsection 4.3.1 and the second one in Subsection 4.3.2 illustrates the advantage of this approach in terms of situation observability with an implementation of the results obtained from the sensor fusion method.

4.3.1. Simulation for the Granular Multi Sensor Fusion Method

The first simulation promotes transitions between various operation conditions. The purpose was to operate under all possible situations so that data could be collected. Human experts were simulated through a prototype granular structure for confidence values greater than 0.1. The purpose of this experiment is to obtain a granular structure similar to the prototype by making use of the methodology presented in Section 3. This example makes use of two sensors: dissolved oxygen(DO) and pH. Possible levels of pH are high, good, or low levels, while DO levels are good or low, resulting in six possible situations. Experts read a different situation every 5 minutes throughout 21 days, allowing for each situation to be monitored every 30 minutes.

4.3.2. Situation Observability in an Implementation

The second simulation presented in this paper explores the transitions triggered by the depletion of kH and the lack of supply from the dosifier pump in the second compartment. This contingency makes the system enter various modes of operation and to operate under different control actions. The kH is consumed the process of nitrification that takes place in the biofilter . The source of kH is inhibited until day five in the simulation; its purpose is to explore the operating condition transitions of the FAM-based agent driving the LED-lamp by observing the time response of the following signals: (1) life support variables, (2) lamp power, and (3) membership values for each situation. The simulations are implemented with a stiff Mod. Rosenbrock numeric method with maximum step of 0.01. Initial conditions are $[DO]$ = 8.4 [mg/L], [CD]=0.69 [mg/L], and [kH]=20 [mg/L]. The simulation time is 240 hours and its initial conditions are in equilibrium with the equivalent concentration of the atmosphere at 22 °C at sea level.

Two control actions driving the LED-lamp are the following: (1) power on and constant at 100% and (2) a proportional-integral controllers with different controlled variables and references, with $P = 200$ and $I = 50$. The Table 5 shows a representation of the operating conditions and the control actions used in each case. These operating conditions result from the combination of the operating ranges of each variable, according to Subsection 2.1. To ensure that the system works correctly, the PI controller employs the error modulation technique presented in [16].

Table 5: Control actions for different operating conditions.

	Low pH	Nom. pH	High pH
Nom. DO	$pH = 6.3$	Nom.	$pH = 8.0$
Low DO	Lamp on	$DO = 3$	DO_{min}

The PI controllers make use of a reference signal with a duty cycle of 18 hours for every 24 to account for the physiological requirements of the botanical elements. For nominal operation, the reference is a squared signal between 6.0 [mg/L] and 5.0 [mg/L], while for the DO_{min} these values are 4.5 [mg/L] and 4.0 [mg/L].

5. Results

5.1. Granular Multi Sensor Fusion Method

The results of the numerical example of the multi-sensor data fusion algorithm are presented in the 3-D graphs of Figure 7. Each situation is defined by a different color for this result and for their associated signals to be shown in the next Subsection. The prototype granular structure is shown in the first 3-D graph. The spatial distribution of the confidence values c_j obtained from the simulated human experts is illustrated in Figure 7(A). The number of data points collected in each situation is not uniform. The PSO aggregation algorithm obtains granules independently of the number of data points, as shown in Figure 7(B). The granules obtained in step (B) are processed with a preliminary coherence operation based on similarity and proximity, resulting in Figure 7(C).

5.2. Implementation of the Granular Approach

The depletion of the kH in the system results in a progressive drop in the pH, which triggers changes in the membership value of the situations read by the FAM

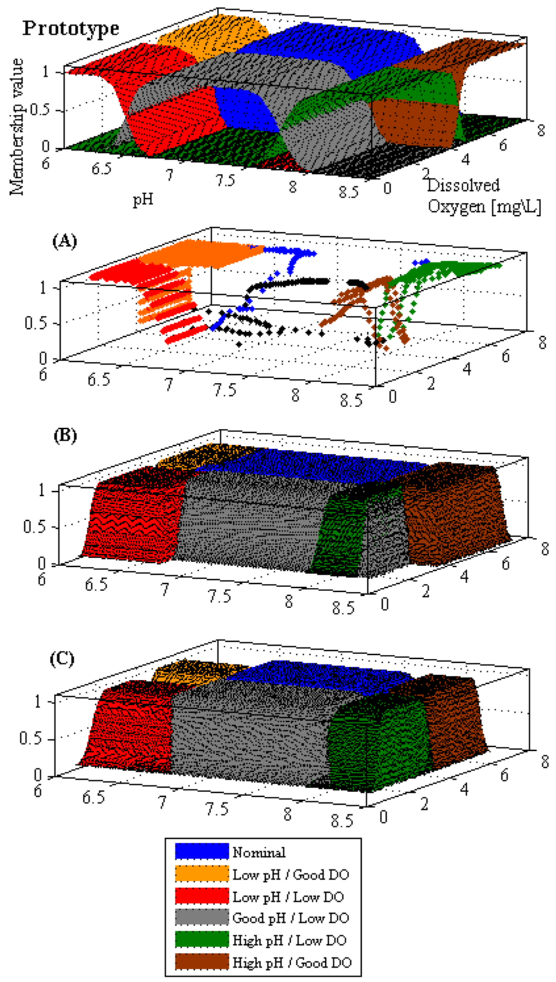


Figure 7: Comparison of the outputs of steps (A), (B), and (C) with prototype granular structure.

during day four, as shown in Figures 8, 9 and 10. The system recovers its nominal values after the kH dosifier pump is enabled in day five. These results show the dynamics of the transitions from three perspectives: (1) the evolution of life support variables, DO and pH, is shown in Figure 8; the behavior of the LED-lamp is presented in Figure 9; and the membership values in the FAM are shown in Figure 10.

6. Discussion

6.1. Observations on the Granular Structures Obtained

The interaction of the simulated humans experts and the system results in lack of uniformity in the distribution of data points collected. Such lack of uniformity introduces holes and overlaps in the granular structures

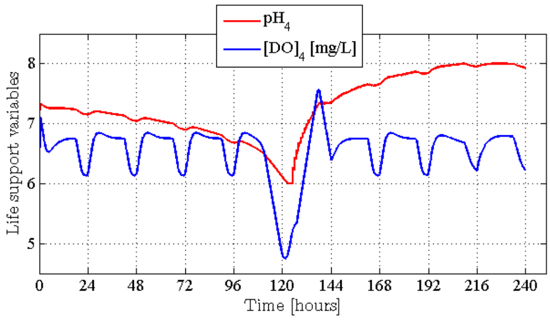


Figure 8: Evolution of the life support variables during the simulation

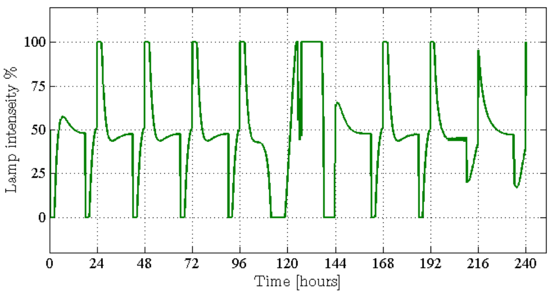


Figure 9: Lamp intensity percentage in response to controllers enabled during the simulation

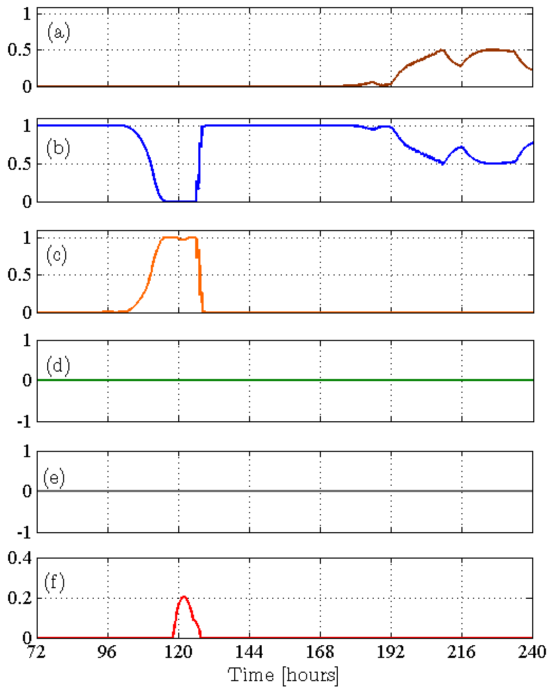


Figure 10: Membership values of the conditions defined in Table 5: (a) Nominal-DO/High-pH; (b) all nominal; (c) nominal-DO/low-pH; (d) low-DO/high-pH; (e) low-DO/nominal-pH; (f) low-DO/low-pH.

obtained by the PSO algorithm. Those holes and overlaps support the need to develop a coherence operation that modifies the parameters of the granules obtained in such a way that may lead to Ruspini partitions in each sensor. The data collection by human experts may influence the effectiveness of such coherence operation. Therefore, future research will spend efforts in defining and characterizing the combination of the aggregation process and the coherence operation. The characterization of these two steps in the methodology proposed will help determine how much data is required from human experts in order to ensure convergence toward Ruspini partitions. The use of better datasets should arrive at solutions without excessive overlaps or holes, as those shown in Figure 7(B). Such result exhibits regularity in the distribution of the granules when compared to the prototype granular structure, even if some situations register a few number of data inputs. One of the advantages of using the PSO algorithm is the flexibility it offers to increase the computational power invested in obtaining granule parameters and to compensate for lack of human expert inputs. This is another question that will be addressed by the characterization of the aggregation process and coherence operation. This is, determining how much may computing power compensate for the lack of human expert inputs in the datasets, by working under different search parameters, particle population sizes, and communication constraints in the PSO.

Another difference between the granular structures obtained and the prototype is in their boundaries or borders. Because the datasets used define the granules obtained, these are not able to address situations beyond those values. In other words, areas not covered by the datasets and granules, i.e. with membership values equal to zero, represent *unknown* situations. This implies that under such conditions a non-expert human operator should be be notified by the monitoring system and be able to request assistance from experts in order to record new assessments. Those boundaries should be in the future identified in the coherence operation, such that a control actions (either manual or automated) may be associated to those regions of the sensing space. The problem of no ensuring complete coverage after the coherence operation translates to situations in which the system may not be controlled either manually or automatically. By developing a coherence operation that addresses these problems, the granular sensor fusion method may be able to start finding applications in real systems.

Other contributions to this granular approach will be found enabling the PSO step to obtain subnormal fuzzy sets, i.e. fuzzy sets with height less than one. Such capacity may allow higher fidelity in representing the confidence values reported by human experts, which may not necessarily include values equal to one. In addition, the ability to define subnormal fuzzy sets may also help to include notions of evidential reasoning in the assessment of unknown situations.

6.2. *Observations from Implementation on the Habitat Model*

From the start of the simulation to about 96 [hours], the system shows consistent temporal responses for DO and lamp power, as shown in Figures 8 and 9. During this period, the pH drops due to the consumption of kH in the biofilter. Without looking at Figure 10, it can be observed that the habitat operates without condition transitions. However, once a transition enters into effect after 96 [hours], it becomes harder to determine in which situation is the system until it goes back into "nominal" on 129 [hours]. The lack of *situation observability* prevents the assessment of the system, even if only two or three signals are used. Hence, an advantage of having a granular structure that allows to identify mode of operation of the system becomes helpful to generate other signals that describe situation transitions. The history of these transitions helps to assess the situation of the system over time, and also enables forensic analysis. This is what Figure 10 presents in the signals (a) through (f).

For example, between 96 [hours] and 129 [hours], the system switches to a different operating conditions before going back to "nominal." The condition that enters into effect before the system is dominantly back to "nomimal" is nominal-DO/low-pH. Under this condition and according to Table 5, the system sets the pH reference value to 6.3. As a consequence, it can be seen in Figure 8 that the DO drops to 4.7 [mg/L] and then is increases to 8.4 [mg/L] (saturation) before going back to nominal. This sudden increase in DO is due to the dynamics of the switching control and the presence of an integral controller. This results suggest that the error modulation technique used[16] may not be sufficient in this case to suppress instabilities introduced by the accumulation in the integration of the PI controller. Note also, that in order to bring down the oxygen level from 8.4 [mg/L] to nominal values [mg/L], the LED-lamp is turned off, as shown in Figure 9, to prevent the plants from generating oxygen and allowing other organisms to consume it. After this transition the system resumes "nominal" operation.

The forensic analysis of Figures 8 and 9 described above is possible to observers because of the information provided by Figure 10. Such information could be displayed in ecological interfaces to support human operators in real-time decision making tasks. Beyond RLSS, the granular decomposition of sensing spaces presented in this paper is applicable to a wider range of complex socio-technical systems. Questions then arise on how to manage high-dimensional sensing spaces and what type of methods are required to make this approach practical. The authors suggest the use of other methods in computational intelligence in combination with FAM to arrive at solutions applicable to larger-scale systems.

7. Conclusions

This paper presented a granular multi-sensor data fusion method that collects assessments from expert human operators to obtain a granular structures that represent their SKB. The purpose of these granular structures is to generate the Ruspini partitions used in the perception function of the FAM-based agent architecture. Although advances in the PSO aggregation algorithm allow to obtain a granular structure consistent with the prototype used, further work is required in the coherence operation of this methodology to arrive at the Ruspini partitions for each sensor. However, the methodology presented in this paper offers an approach to overcome the combinatorial explosion of merging information from a large number of sensors by exploiting human-system interaction. Expert assessments define the operational condition of the system with a subjective assessment of its situation. Future work will also focus on obtaining subnormal fuzzy sets to approximate better the information reported by human experts. This will allow to address not fully known situations and may help to incorporate notions in evidential reasoning. Simulations performed on the aquatic habitat show how situation-rich signals help to increase situation observability of these systems.

[1] Eckart, P., *Spaceflight Life Support and Biospherics*, Microcosm Press and Kluwer Academic Publishers, USA, 2nd ed., 2010.

[2] Sheridan, T. B., *Humans and Automation: System Design and Research Issues*, John Wiley & Sons, Inc., New York, NY, USA, 2002.

[3] McCoy, T., Flint, S., Straub, J., Gazda, D., and Schultz, J., "The Story Behind the Numbers: Lessons Learned from the Integration of Monitoring Resources in Addressing an ISS Water Quality Anomaly," *41st International Conference on Environmental Systems*, 2011.

[4] Drayer, G. and Howard, A., "A Granular Approach to the Automation of Bioregenerative Life Support Systems that Enhances Situation Awareness," *Proceedings of the 2nd IEEE Conference on Cognitive Methods in Situation Awareness and Decision Support*, IEEE Xplore, March 2012.
[5] Eberhart, R. C., Kennedy, J., and Shi, Y., *Swarm Intelligence*, Morgan Kaufmann, 2001.
[6] Endsley, M. and Jones, D. G., *Designing for situation awareness: an approach to user-centered design.*, Taylor & Francis Group, 2nd ed., 2012.
[7] Durrant-Whyte, H. and Henderson, T. C., *Springer Handbook of Robotics*, chap. 25, Springer-Verlag Berlin Heildelberg, 2008, pp. 585–614.
[8] Ross, T., *Fuzzy Logic with Engineering Applications*, John Wiley & Sons, 2nd ed., 2004.
[9] Shafer, G., *A Mathematical Theory of Evidence*, Princeton University Press, 1976.
[10] Kohlas, J. and Monney, P.-A., *A Mathematical Theory of Hints: An Approach to the Dempster-Shafer Theory of Evidence*, Springer-Verlag Berlin Heidelberg, 1995.
[11] Yager, R. R. and Liu, L., editors, *Classic Works of the Dempster-Shafer Theory of Belief Functions*, Springer-Verlag Berlin Heidelberg, 2008.
[12] Drayer, G. and Howard, A., "A FAM-based Switched Control Approach for the Automation of Bioregenerative Life Support Systems," *41st International Conference on Environmental Systems*, AIAA, Portland, Oregon, July 2011.
[13] Liberzon, D., *Switching in Systems and Control*, Birkhäuser, 2003.
[14] Zadeh, L., "Fuzzy sets," *Information and Control*, Vol. 8, No. 3, 1965, pp. 338 – 353.
[15] Ruspini, E. H., "A new approach to clustering," *Information and Control*, Vol. 15, No. 1, 1969, pp. 22 – 32.
[16] Drayer, G. and Strefezza, M., "Integral Control with Error Modulation in a FAM-based Agent for a Furuta Inverted Pendulum," *2008 IEEE World Congress on Computational Intelligence*, Hong Kong, June 01-06 2008, pp. 1590–1597.
[17] Hespanha, J. P., Liberzon, D., and Morse, A. S., "Overcoming the limitations of adaptive control by means of logic-based switching," *Systems & Control Letters*, Vol. 49, No. 1, 2003, pp. 49 – 65, Adaptive Control.
[18] Yao, Y., "Perspectives of Granular Computing," *Proceedings of 2005 IEEE International Conference on Granular Computing*, Vol. 1, 2005, pp. 85–90.
[19] Doan, A., Ramakrishnan, R., and Halevy, A. Y., "Crowdsourcing systems on the World-Wide Web," *Commun. ACM*, Vol. 54, April 2011, pp. 86–96.
[20] Prestopnik, N. R. and Crowston, K., "Gaming for (Citizen) Science: Exploring Motivation and Data Quality in the Context of Crowdsourced Science through the Design and Evaluation of a Social-Computational System," *e-Science Workshops, IEEE International Conference on*, Vol. 0, 2011, pp. 28–33.
[21] Drayer, G. and Howard, A., "Design, Modeling and Simulation of a Reconfigurable Aquatic Habitat for Life Support Control Research," *41st International Conference on Environmental Systems*, AIAA, Portland, Oregon, July 2011.
[22] Timmons, M. and Ebeling, J., *Recirculating Aquaculture*, North Eastern Regional Aquaculture Center, 2007.